Improving Lidar Data Evaluation for Object Detection and Tracking Using a Priori Knowledge and Sensorfusion

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Abstract: This paper presents a new approach to improve lidar data evaluation on the basis of using a priori knowledge. In addition to the common I- and L-shapes, the directional IS-shape, the C-shape for pedestrians and the E-shape for bicycles are introduced. Considering the expected object shape and predicted position enables effective interpretation even of poor measurement values. Therefore a classification routine is utilized to distinguish between three classes (cars, bicycles, pedestrians). The tracking operation with Kalman filters is based on class specific dynamic models. The fusion of radar objects with the used a priori knowledge improves the quality of the lidar evaluation. Experiments with real measurement data showed good results even with a single layer lidar scanner.

1 INTRODUCTION

The computational detection and interpretation of the environment in traffic scenes have become more and more important in recent years. An increasing amount of advanced driver assistance systems (ADAS) utilize environmental data, e.g. collision warning or lane detection systems. Among radar sensors, ultrasonic sensors, cameras and others, lidar-sensors are typically used for perceiving the automobile's environment.

Lidar scanners produce distance measurement values without providing any further information. To process these, there are generally two different approaches for lidar data evaluation. The first is based on an occupancy grid map created using simultaneous localization and mapping (SLAM) techniques (Vu et al., 2007). Dynamic objects can then be identified by comparing the lidar measurement with the calculated occupancy grid map.

The second approach usually consists of two separate steps: 1) the extraction of geometric features in the lidar measurements and 2) a tracking based on these features. The identification of relevant objects in the cloud of measurement values is a challenging task and has been covered in numerous publications (Fortin et al., 2012),(Kaempchen et al., 2005),(Lindl, 2008),(Sparbert et al., 2001),(Mendes et al., 2004),(Fayad and Cherfaoui, 2007),(Fuerstenberg et al., 2003). The detection of vehicles is mainly based on the assumption of an almost rectangular shape. Therefore, the measurement values are searched for characteristic line segments. Fortin (Fortin et al., 2012) presents a feature extraction method based on geometric invariants. Kaempchen (Kaempchen et al., 2005) has improved this procedure by differentiating between different object representations. Cars appear in the lidar data in the form of the characteristic object I-, U- and L-shapes, which can be fitted into the measurement values to find possible objects. These characteristic shapes are then tracked over several time steps.

Sometimes, object points cannot be detected for several reasons, e.g., reflections of the laser beam, dark surfaces in combination with great distances, occlusion of the object or angular resolution. Within these corrupted measurements, a meaningful feature extraction is often not possible because there are no characteristic shapes or the shapes have changed.

We have now developed a novel approach to use the knowledge about tracked objects from previous measurement steps and other sensors to evaluate the raw data.

This is illustrated in figure 1(a), which shows an extract of lidar measurements from a real traffic scene. Without any further information, the scene is difficult to interpret. But considering the object position and dimensions from previous steps, the actual position of the object, an oncoming car, can be evaluated, as shown in figure 1(b). The novelty of our approach consists of the usage of the a priori knowledge di-

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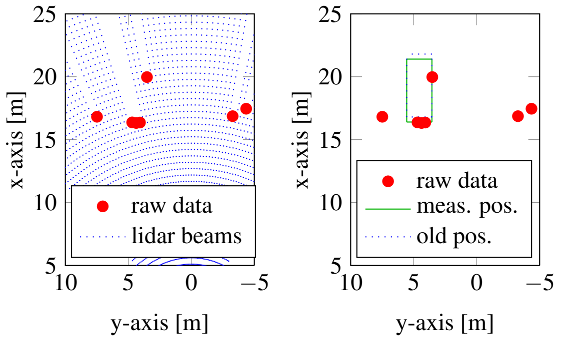


(a) only raw data (b) with a priori knowledge

Figure 1: a) A lidar measurement insufficient for effective feature extraction and b) interpretation by using a priori knowledge.

rectly on the raw measurement values. Thus the corresponding measurement values can be interpreted correctly and used for the object update, even if there were only very few points detected on the object and therefore no features are extractable with common lidar interpretation approaches. If a priori knowledge about an object is not available, a common approach is used as explained in section 3.3.

Before the single steps and models of the developed approach are explained in detail, the modeling of traffic participants is described in 2. The novel lidar evaluation routine is presented in section 3, the classification of traffic participants in 4 and the tracking management in section 5. In section 6 the sensorfusion with the radar sensor is described. The paper finishes with an explanation of some experimental results and a conclusion.

2 OBJECT MODELS

Mathematical models for the geometry and the dynamics of the objects are necessary for detection and tracking. For a more precise description, we differentiate between three classes of traffic participants: cars, bicycles and pedestrians, and a class "unknown" for not yet classified objects.

2.1 Dynamic Models

To describe the dynamics of car objects, it is assumed that only movement heading in forward direction is possible. Therefore the approximated middle of the rear axis is chosen as a reference point. The object state is described by the position x, y, velocity v, acceleration a, orientation ψ and yaw rate $\dot{\psi}$. Lindl (Lindl, 2008) describes the derivation of the equation of motion with respect to the mentioned constraints.

The resulting difference equation is simplified for an efficient modeling of the dynamics, leading to

$$\mathbf{x}_k = \begin{bmatrix} x \\ y \\ \psi \\ v \\ \dot{\psi} \\ a \end{bmatrix}_k = \mathbf{x}_{k-1} + \begin{bmatrix} cos(\psi)v\Delta T \\ sin(\psi)v\Delta T \\ \dot{\psi}\Delta T \\ a\Delta T \\ 0 \\ 0 \end{bmatrix} . \quad (1)$$

ΔT describes the length of a time step and corresponds to the time difference between two consecutive lidar measurements.

The dynamics of bicycles are modeled on the same assumption that motion is only possible in forward direction and therefore lead to the same movement model (1).

Pedestrians can move independently from their heading direction. Therefore the dynamics are modeled with a simple point mass model, allowing independent movement in both coordinate directions:

$$\begin{bmatrix} x \\ y \\ v_x \\ v_y \end{bmatrix}_k = \begin{bmatrix} 1 & 0 & \Delta T & 0 \\ 0 & 1 & 0 & \Delta T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ v_x \\ v_y \end{bmatrix}_{k-1} \quad (2)$$

As pedestrians rarely show longer maneuvers with a specific acceleration, the movement model only includes the velocities. Abrupt velocity changes typical for pedestrian movement can be adequately represented with the process noise and so no further states are required for the modeling.

The dynamics of objects, which are not (yet) classified, are modeled as in (2) but extended by the orientation, which is necessary for the car and bicycle representations.

2.2 Geometric Models

The car class covers most vehicles as cars and buses. As geometric representation a rectangular contour is assumed, which is common practice ((Kaempchen et al., 2005), (Lindl, 2008)) and eligible for most cars and buses. The complete contour of these objects thus can be described by five variables

$$\mathbf{x}_{shape,c} = [x, y, \psi, l, w]^T . \quad (3)$$

Here, x, y represent the position, ψ the orientation and l, w the length and width of the object. Due to the operational principle of the lidar scanner, a maximum of two sides of the rectangular contour can be detected in one scan. Thus, characteristic I- and L-shapes are found in the measurement data. By describing the expected positions of the measurement values, these shapes play an important role in the evaluation.

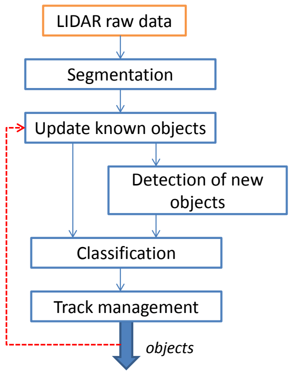


Figure 2: Overview over the essential steps of the presented approach including the feedback of the object information.

Bicycles have no such characteristic shape which can easily be found in the lidar measurements. Through the permeable structure of a bicycle and the changing foot positions the resulting detected values cannot be foreseen. Consequently, the common approach to feature detection has its limits.

However, the presented approach is not absolutely reliant on such characteristics and therefore also allows the tracking of bicycles. Based on real lidar measurements of bicyclists, we found that these can be represented best by an ellipse with arbitrary measurement points inside. This can be represented with the same variables as in equation (3), where l and w now describe the length of the ellipse axes.

Similar to bicycles, pedestrians do not result in a characteristic shape in the lidar data. However due to their small dimension they can be identified and differentiated from background objects more easily. That's why they can be tracked using the common approach as can be seen in (Kaempchen et al., 2005) or (Lindl, 2008). Accordingly, pedestrians are represented by circular shapes which can be described with just three variables:

$$\mathbf{x}_{shape,p} = [x, y, r]^T \, . \tag{4}$$

Here x, y represent the position and r the radius. Because of their independent moving no orientation is needed.

3 Lidar EVALUATION

As can be seen in figure 2 the presented approach consists of several separate steps. This section describes how the lidar data is processed, corresponding to the three steps segmentation, evaluation of known objects and the detection of new objects.

3.1 Segmentation

Motivated by the high number of measurement values created by lidar scanners, a preprocessing of the data is used. Since consecutive processing steps are based directly on the raw measurement values, only a rough grouping is needed. The aim of this step is to group all measurements belonging to the same real objects together. As in (Sparbert et al., 2001) or (Mendes et al., 2004) the values are clustered using a simple distance criterion. To keep processing as effective as possible, the segmentation uses the raw polar coordinates provided by the lidar scanner. A geometrically motivated threshold is used, considering the increasing probability of non-detection with smaller angles between the laser beams and the detected surface. We assume that surfaces with an angle beneath 10 degrees are unlikely to be detected. I.e. two consecutive measurement points are grouped together if the angle between them and the laser beam is greater than this threshold.

3.2 Evaluation of Known Objects

As announced in the introduction, the usage of a priori knowledge to improve the lidar evaluation is the idea of the presented approach. As can be seen in figure 2, the a priori knowledge, consisting of known objects from the last time step (dotted arrow), is combined with the clustered raw data. To avoid information loss, no further preprocessing is used than the segmentation.

3.2.1 Projection of a Priori Knowledge

The information about old objects can include the geometric and dynamic information mentioned in section 2. Apparently the quality of these variables depend on the history and maybe not all of them could be detected yet, e.g. the length of a car driving in front. Based on the existing information about old objects, the expected shape of these can be projected to the actual coordinate system of the sensor. In addition to the motion of the own vehicle, it is necessary to consider the motion of the objects. Information about the dynamics instance to compensate the ego-motion can be gained from the vehicle ESC controller. The expected motion of the objects is calculated during the filtering process.

3.2.2 Association

Next, the segments of lidar measurements are associated to the expected shape of the known objects. Therefore, it is tested whether the points of the segments lie within a reasonable area around the shape,

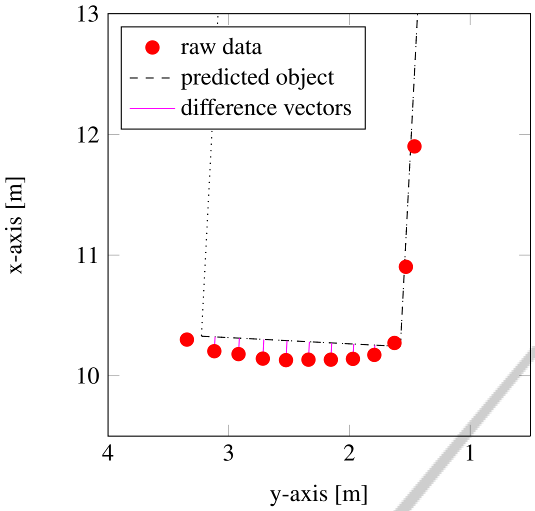


Figure 3: Evaluation of lidar raw data considering the predicted object shape leading to the deviations of the measurement values used for the position update.

i.e. near the expected object border and on the viewable side. To avoid unnecessary computations, only segments are tested which lie within the same viewing angle as the expected object. Ideally, every object is associated with one segment, but through occlusions or interrupted detection caused by partly insufficient remission some objects could be represented by more than one segment.

3.2.3 Detectable Shapes

The measurement values of the matching segments are now interpreted considering the expected object shape. Therefore it is more like a correction of the expected shape by means of the measured values. In figure 3 the situation of an oncoming car is shown with the expected shape and the measured values. The lidar scanner position is in the origin of the coordinate system and therefore only the two dashed black sides of the shape are expected to be measured, whereas no measurement values should appear on the dotted back side. To take into account the limited visibility of the car object contours, three shapes are differentiated for the description of the expected measurement values, the I-, the IS- and the L-shape as illustrated in figure 4(a)-(c) with real measured lidar values. The names of the I- and L-shapes correspond to the represented form. Consequently, the I-shape represents a straight line in the measurement values and the ”L” two perpendicular ones. These two are commonly used ((Lindl, 2008), (Fayad and Cherfaoui, 2007)) to represent the situation with one or two visible sides, sometimes supplemented by a U-shape for a rounded vehicle front or back (Kaempchen et al., 2005). Because of the rarity of such U-shapes in the examined data, this shape was neglected. The developed approach, however, enables the usage of the novel IS-shape, which is used for representing the side of a car and therefore a distinction between side and rear or front (I-shape) is possible. In figure 4 the dotted line marks the expected movement direction of the objects, which depicts the difference between (a) the back side and (b) the side of a car. With the evaluation of the lidar data being slightly different depending on the considered shape, it is reasonable to make this distinction due to the expected movement parallel or perpendicular to the shape. As bicycles and pedestrians are assumed to be detected as arbitrary distributed points, these are only represented by the so called C-shapes (cylinder), and E-shapes (ellipse) as in figure 4(d),(e).

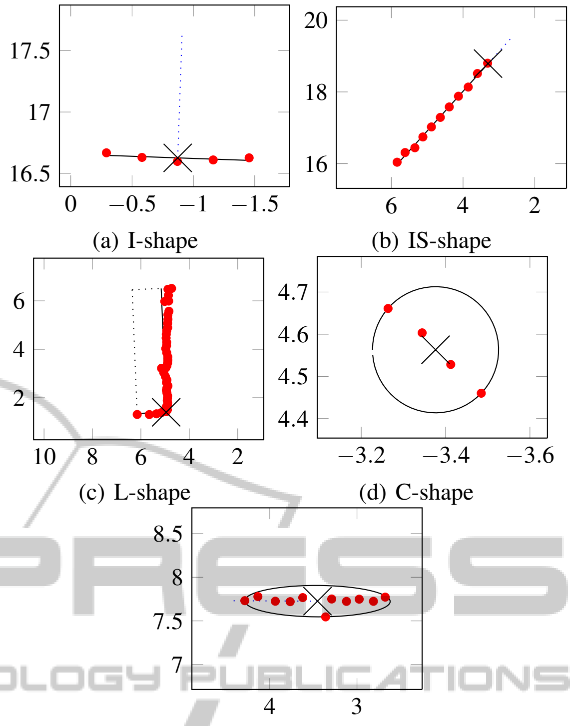


Figure 4: Characteristic segment shapes of real measured objects: a) back side of a car, b) side of a car, c) front and side of a car, d) pedestrian, e) bicycle. All axes are in meters and the lidar scanner is positioned in the origin of the coordinate system.

3.2.4 Evaluation of Measurement

The aim of the lidar evaluation is to find the actual geometric object states defined in one of the equations (3) and (4). Therefore the predicted shape, presented in the last paragraphs, is compared with the corresponding raw measurement values. By calculating the deviations of the measurement values from the shape, the object state can be corrected.

First the position difference is calculated by the mean perpendicular distance of all corresponding measurement values to one side, as shown in figure 3. In this example, the expected shape is too far away because the velocity of the object was underestimated. Moving the shape by the mean of the pink, solid difference vectors leads to an average match of the measurement points. Note that most measurement values correspond to only one side and therefore only those difference vectors to the corresponding side are accounted for. By using the perpendicular distance consequently, only motion perpendicular to the car's side is considered. Therefore the same procedure is used on the other visible side to get the measured object position. Obviously this is problematic for the one-sided I- and IS-shapes. Especially for IS-shapes, movement parallel to the shape is expected and is therefore measured through the motion of the shape ends. However, this is not as precise as the difference measurement because the beam directions of the lidar scanner lead to a discrete measurement accuracy perpendicular to the beams. Compared to the I-, IS- and L-shapes, the position update for C- and E-shapes is relatively easy. If the measured values match the dimension thresholds defined for pedestrians or bicycles, the calculated center of gravity is used as the position.

Second, the orientation of the measured shape is determined. In case of an I-, IS-, L- or E-shape the orientation is calculated using regression lines fitted into the measurement points (cf. (Lindl, 2008)). To avoid corruption through short sides and round object shapes, some additional characteristics, such as side lengths and matching quality of the corner point, are considered. Especially the determination of the orientation of bicycles is often problematic. In such cases, the orientation is not measured using the lidar points but determined during the filtering process.

Finally, the dimensions of the objects are adapted. Therefore the dropped perpendicular bases of the end points are taken into consideration. These are determined anyway at the same time as the heading calculation. As the lidar scanner cannot detect the complete dimensions of an object in every measurement step because of occlusion or deficient remission, the measured dimensions vary over time. To overcome these deviations, the dimensions could be filtered as in (Fayad and Cherfaoui, 2007). However, to prohibit the shrinking of an object over time when it is only partly detected, we simply keep the maximum of measured and previous dimensions like in (Fuerstenberg et al., 2003).

3.2.5 Changes in Representing Shapes

An important phenomenon when tracking dynamic objects with lidar measurements is that the detected shape varies depending on the orientation and distance to the lidar scanner. Since objects are represented here using five characteristic I-, IS-, L-, C- and E-shapes, it is important to detect when another shape fits better. This enables optimal interpretation of the measurement values. A good example for changing representations is an overtaking car, whose shape changes from “IS” to “L” and finally to “I”. To detect such transitions, special areas around these shapes are defined, e.g. for the IS-shape the area where the second side is expected. If measurement points exist inside these regions, the shape is switched. This also holds for the C- and E-shape, which normally change when the dimensions of the tracked object exceeds the thresholds for pedestrians or bicycles.

3.3 Detection of New Objects

At the beginning of the tracking process or if an object enters the surveillance zone of the sensor, there is no previous information available. Therefore the presented approach has to distinguish between the tracking of known objects, as presented in the previous section, and the detection of new objects.

The sequence of the object processing is known from figure 2. First, all known objects are processed and only the unassociated segments are passed onto the detection step. Here, possible traffic participants have to be identified. This is done using the common approach (Kaempchen et al., 2005), (Lindl, 2008), where the measurement data is searched to identify characteristic shapes. We try to find segments which match the introduced C-, I-, IS- and L-shapes. The first is characterized by a small expansion of $0.9\,m$ at most and possibly represents a pedestrian. The latter have to be approximated with one or two regression lines respectively and the regression error has to be below a threshold. Finally the dimensions of the shapes have to match the tolerated dimensions of traffic participants shown in table 1. Note that the bicycle shape “E” is missing for the creation of new objects. Since this shape is very unspecific, motivated by the varying measurements of bicyclists, there are not enough special characteristics to search for. To avoid numerous false detections, this shape has been excluded and bicycle objects are created through shape changes of dynamic objects.

Table 1: Tolerated dimensions of traffic participants.

traffic participants	length	width	shape
car, van	$2-6m$	$0.9-2m$	I,IS,L
truck, bus	$6-19m$	$0.9-3m$	I,IS,L
pedestrian	-	$0.25-0.9m$	C

4 CLASSIFICATION

With this approach, the four classes car, bicycle, pedestrian and unknown are distinguished as mentioned in section 2. This enables both, an improved tracking performance by improved matching dynamic models and a differentiated visualization in the developed predictive display.

The classification is based on the evaluated properties of the objects. From the evaluation of the lidar measurements, the size, orientation and shape of the object are available. The speed and direction of motion are derived by the filtering process described in the next section. For the classification there is one weighting function for each known property similar to (Mendes et al., 2004). An example of the chosen weighting functions for the class car is shown in figure 5. The length, width, shape, velocity and the angle between motion direction and orientation are taken into consideration. Note, that some functions have higher weights corresponding to their importance. Depending on the values of each object in these categories, a current class agreement is calculated as a mean value of all weights $w_{i,c}$ with $i = 1...5$. Class probabilities γ_{class} are deducted from these values considering the normalization $\sum_{classes} \gamma_i = 1$ and smoothing the class changes. All new objects are initialized as unknowns and change their class if γ_{class} exceeds a specific threshold.

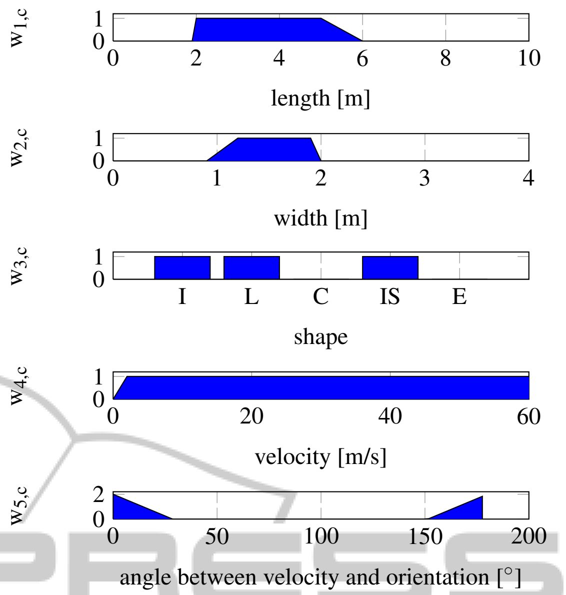


Figure 5: Classification weighting functions for class car to determine the class agreement.

5 TRACKING MANAGEMENT

The tracking management mentioned in figure 2 consists of two important steps. First, the deletion of objects and second, the tracking of the objects by means of a filter.

5.1 Deletion of Objects

In addition to detecting and tracking new objects, it is important to delete objects. There are two main reasons for deletion. The first deals with vanishing objects, which leave the surveillance zone or are occluded by other objects. Therefore targets are deleted after they haven't been detected for a specific period of time. The second covers the cleanup of erroneous objects. Such can result from misleading shapes due to the vegetation beside the road. False objects can be detected by measurement points inside the assumed solid area, unrealistic motion or exceeding dimensions.

5.2 Tracking

For the tracking of the detected traffic participants, different kalman filters are used for the different motion models (cf. (Grewal and Andrews, 2008)). Based on the motion models presented in section 2, the filter calculates the optimal solution for the object states considering the measured values and the assumed noise terms. The nonlinear dynamic model for cars and bicycles is processed by an extended kalman filter. Deviating from the presented process in figure 2, the prediction step of the kalman filter is already used to calculate the expected object shape for the lidar evaluation.

6 ENRICHMENT OF A PRIORI KNOWLEDGE THROUGH SENSORFUSION

The presented approach uses a priori knowledge to effectively interpret the raw data of the lidar scanner. Therefore the detection quality depends on the amount of a priori knowledge. Consequently the enrichment of the knowledge through additional information from other sensors increase the quality of the lidar evaluation.

Here we used the radar sensor installed with the series ACC to insert additional knowledge of the detected scene. The extended functional overview is illustrated in figure 6. The object list provided by the radar sensor with its integrated processing and tracking is filtered for relevant dynamical objects to add them to the knowledge base. Within the knowledge fusion step the radar objects are integrated into the lidar representation of the environment also regarding synchronization purposes. As our developed sensor data fusion combines different fusion levels, namely the radar data from the object level and the lidar values from the raw level, we labeled it 'mixed fusion'.

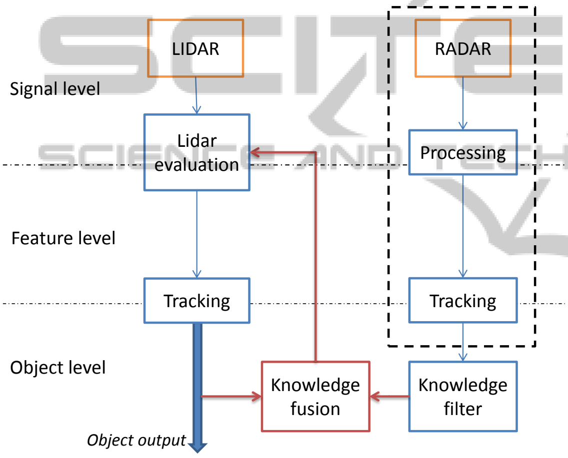


Figure 6: Combination of the signal and the object level in the "mixed fusion".

A big advantage of the presented fusion approach is the early possible combination of both sensors. With the a priori knowledge of the radar, the precise distance measurement of the lidar can be used to correct the object position as soon as the first measurement point is available. Since the lidar evaluation is based on the raw data and therefore not dependent on extensive object shapes.

Regarding an oncoming car as example, the radar detects the approximate position and a precise relative velocity in distances up to $150m$ and enables an early car classification indicated by the objects velocity and its conductibility since it is detected by the radar. As soon as the car enters the smaller range of the lidar, the position can be corrected, even if there are only single measurement points detected, which would not lead to a detected object in a feature based lidar evaluation.

7 EXPERIMENTAL RESULTS

The presented approach was implemented and tested with recorded lidar and radar data. The test vehicle was an AUDI Q7 with a one-layer SICK lidar scanner with $75Hz$ frequency, $1°$ angular resolution, $180°$ opening angle and a maximum range of $80m$, which was mounted on the front at about $0.5m$ height. The used Radar sensor is the series ACC long range radar with an approximate range of $150m$ and an horizontal opening angle of about $\pm 8°$.

Precise reference data is necessary for an objective and extensive system evaluation of an environment surveillance system. However, no such data sets were available and therefore the system performance was evaluated optically by means of video sequences of existing traffic scenes. The information of the environment surveillance system is therefore projected into video images and thus a quick evaluation is possible. In figure 7, two different recorded traffic scenes with the detected object shape and the expected future position 500 milliseconds ahead are visualized. Therefore, it is possible to evaluate simultaneously the object detection and the motion tracking by optical survey. To enable the calculation of objective quality criteria for detection, the measurement data has been manually attributed by marking the time sequences where the actual traffic participants are located in the surveillance zone. To that end, the detection rate, false detection rate, false classification rate and temporal coverage ((Lindl, 2008, p.150)) of five different traffic sequences (city, rural, highway) were evaluated. The images in figure 7 are snapshots of the both city scenarios. Each value was calculated separately for the detection with the lidar sensor only and the fusion of lidar and radar. The calculated criteria and the length of the datasets are listed in table 2. The detection rates (DR) indicate, that most objects are detected and classified correctly. Comparing the DR and the TC values of the two different sensor configurations, the major improvement through the integration of the radar can be seen. Especially in the rural scenarios with fast, oncoming traffic the small detection rate of the lidar leads to a short temporal coverage of these objects. In combination with the radar, the cars are tracked early and a smooth transition to the lidar monitored area is enabled, leading to high detection rates ($94-100\%$).

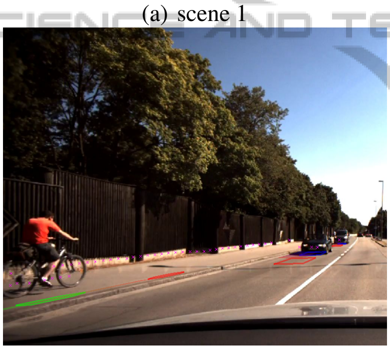
8 CONCLUSION AND OUTLOOK

We presented a novel approach for evaluating lidar scanner raw data regarding the detection and track-

Table 2: Calculated quality criteria for lidar only and lidar radar fusion: detection rate (DR), false classification rate (FCR), false detection rate (FDR) and temporal coverage (TC).

criteria		city 1 (65 s)		city 2 (46 s)		rural 1 (79 s)		rural 2 (60 s)		highway (59 s)	
		K_{Lid}	K_{Fus}	K_{Lid}	K_{Fus}	K_{Lid}	K_{Fus}	K_{Lid}	K_{Fus}	K_{Lid}	K_{Fus}
DR	[%]	0.81	0.81	0.93	1.00	0.65	1.00	0.63	0.94	0.83	0.92
FCR	[%]	0.13	0.13	0.00	0.00	0.05	0.00	0.06	0.06	0.00	0.00
FDR	$[\frac{1}{s}]$	0.69	0.72	0.77	0.77	0.18	0.19	0.73	0.78	0.12	0.14
TC	[%]	0.36	0.37	0.42	0.65	0.26	0.87	0.19	0.67	0.36	0.87

(a) scene 1



(b) scene 2

Figure 7: City traffic scenes with projected detecting and tracking results through grounded shapes illustrating the detected positions and predicted future positions 500 milliseconds ahead.

ing of traffic participants. It is based on the usage of knowledge over objects to improve the lidar raw data evaluation. The integration of the radar sensor for additional object information shows an considerable improvement to the detection performance. This approach also enables the tracking of undefined shapes like bicycles. For precise tracking, cars, bicycles and pedestrians are differentiated by a classification routine and therefore different dynamic models are applied.

The approach is based on the a priori knowledge about objects and therefore the performance depends on the amount of information available. Consequently, the integration of additional information sources will lead to a further improvement. Furthermore, the extension of the classification schema with other classes like trucks would widen the area of application.

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